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Price volatility spillover of Indian onion markets: A comparative study

KANCHAN SINHA[1], SANJEEV PANWAR[2], WASI ALAM[3], K N SINGH[4], BISHAL GURUNG[5], RANJIT KUMAR PAUL[6] and ANIRBAN MUKHERJEE[7]

ICAR-Indian Agricultural Statistics Research Institute, New Delhi 110 012

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ABSTRACT

To investigate the interdependence between Indian onion markets in terms of price volatility, the present study was conducted in four different vital onion markets in India, viz. Mumbai, Nashik, Delhi and Bengaluru. The long term monthly data, from March, 2003 to September, 2015 was collected from the website of agmarknet.nic.in. We have employed the VEC-MGARCH model to estimate mean and volatility spillover simultaneously among the different markets and also examined the nature of dynamic correlation using the DCC model. The presence of mean and volatility spillover was found between the markets. This type of significant interaction between the volatility of different markets is highly useful for cross market hedging and for sharing of common information by market participants. The empirical results also suggest for a very close observation on different market behavioral pattern since, "news" in one market may impact other market through the number of interdependencies.

Key words: Dynamic conditional correlations, Market behavior, Price volatility spillover, VEC-MGARCH

Onion is one of the most important vegetable crops for household consumption and also for foreign exchange earner among the fruits and vegetables on contrary to the financial market where it is considered as a most sensitive commodity due to sudden price fluctuation. India covers an area of 1.064 Million hectare (Mha), with production of 15.118 Million tonnes (MT) and is the 2nd largest producer of onion, next only to China. Maharashtra (4.9 MT) is the largest onion producing state followed by Karnataka (2.5 MT), Gujarat (1.5 MT), Bihar (1.08 MT), Madhya Pradesh (1.02 MT) and Andhra Pradesh (0.8 MT). Around 97% of the country's onion harvest is sold in 50 major onion market yards, regulated under the Agricultural Price Monitoring Act (APMC).

Due to fluctuation in price and unstable production, onion is considered as one of the most volatile agricultural commodity. The sudden increase in onion market price affects both producers as well as consumers through a spillover effect to the other onion markets which leads to high inflation in the economy. For the market participants, one of the important tasks is to know about shocks and volatility transmission mechanism which can spread instantaneously from one market to another market for price regulation and policy formulation. In this background, an attempt was made to examine price volatility and shock transmission mechanism between major Indian onion markets. We consider price variance relationship between markets can help in policy formulation. In other sense, increase in price volatility negatively affects the welfare of developing country like India where agricultural commodities form the basis for household income and food consumption.

Volatility estimation in agricultural commodity prices has become now days a common phenomenon. Since the seminal work by Engle (1982) and Bollerslev (1986), there are several applications of GARCH and its family of models for modeling volatility in crop yield and agricultural commodity prices (Paul *et al*. 2009, Paul *et al*. 2014). However, besides studying volatility, price discovery and risk transfer are considered to be two important contributions of futures market towards the organization of economic activity (Garbade and Silber 1983). Price discovery refers to the use of future prices for pricing cash market transactions. It means futures price serves as markets expectations of subsequent spot price. Chopra and Bessler (2005) studied the incidence of price discovery for black pepper in the spot market and the nearby and first distant futures markets in Kerala, India whereas, Patnaik (2013) applied dynamic conditional correlation model in the foreign exchange rates of the Indian rupee and four other prominent foreign currencies to measure volatility spillover across these exchange rates. Padhi and Lagesh (2012) studied volatility transmission between five Asia equity markets, India and US while Malik and Ewing (2009)

[1](e mail: kkiasri@gmail.com), ICAR-IASRI, New Delhi. [2]ICAR , HQ, Krishi Bhawan, New Delhi. [7]Social Science Section, ICAR-Vivekananda Parvatiya Krishi Anusandhan Sansthan, Almora Uttarakhand 263 601.

studied volatility transmission between oil prices and five different US equity sector indexes. Chevallier (2012) studied dynamic nature of correlation among oil, gas and CO_2 of European climate exchange using Bloomberg and Reuters dataset employing BEKK, CCC and DCC models and Lin and Li (2015) studied price and volatility spillover effect of monthly data of natural gas of US, Europe and Japan in a VEC-MGARCH model framework. Modern time series methods like cointegration reflect the price transmission mechanism between futures and spot market (Paul and Sinha 2016).

MATERIALS AND METHODS

The methodological approach has been started by testing for stationarity using Augmented Dickey Fuller (ADF) test given by Said and Dickey (1984). The test for the variable (say) y_t can be expressed in a following manner:

$$\Delta y_t = \alpha + \gamma t + \rho y_{t-1} + \beta \sum_{i=1}^{p} \Delta y_{t-i} + e_t \tag{1}$$

where, y_t is a vector to be tested for cointegration, t is time or trend variable, $\Delta y_t = yt - y_{t-1}$ and e_t is a white noise process. The null hypothesis that $\rho = 0$; signifying unit root, i.e. the time series is non-stationary and the alternative hypothesis $\rho < 0$ is signifying the time series is stationary, therefore, rejecting the null hypothesis.

After taking the nonstationarity into account, we need to identify the optimal length for an unrestricted vector autoregressive (VAR) model (with a maximum lag number of eight) on the basis of suitable information criteria. A VAR model is a generalization of univariate autoregressive model that is a vector of time series. The right hand side of each equation in a VAR model includes a constant and lags of all the variables in the system. A two variable VAR with one lag can be written as:

$$x_{1,t} = c_1 + \varphi_{11,1} x_{1,t-1} + \varphi_{12,1} y_{2,t-1} + \varepsilon_{1,t} \tag{2}$$

$$x_{2,t} = c_2 + \varphi_{21,1} x_{1,t-1} + \varphi_{22,1} y_{2,t-1} + \varepsilon_{2,t} \tag{3}$$

Where ε_{1t} and ε_{2t} are white noise processes that may be contemporaneously correlated. Coefficient $\varphi_{ii,l}$ captures the influence of l^{th} lag of variable x_i on itself. While coefficient $\varphi_{ij,l}$ captures the influence of l^{th} lag of variable x_j on x_i.

After that, to identify the cointegration relation between the two price series, two likelihood ratio tests employed such as λ_{trace} and λ_{max} respectively.

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} ln\left(1 - \hat{\lambda}_i\right) \; for = 0,1...,n-1 \tag{4}$$

$$\lambda_{\max} = -T \; ln\left(1 - \lambda_{r+1}\right) \tag{5}$$

where, T is the number of usable observations and $\hat{\lambda}$ are the estimated eigen values (also called characteristics roots). The trace test statistic (λ_{trace}) tests the null hypothesis of r cointegrating relation against the alternative hypothesis of less than or greater than r cointegrating relation while, the λ_{max} test statistic tests the null hypothesis of r cointegrating relation against $r+1$ cointegrating relations. The rank of II can be determined by using λ_{trace} or λ_{max} test statistic. If, rank of $II = 1$, then there is single cointegrating vector and II can be factorized as $II = \alpha\beta$, where α and β are 2×1 vectors represent error correction coefficients measuring the speed of convergence and cointegrating parameters respectively.

If price series are cointegrated we can estimate the vector error correction model that can be seen as a restricted VAR model including a variable representing the deviations from the long-run equilibrium. Johansen's (1988) Vector Error Correction Model (VECM) is employed to investigate the causal relationship between prices. Equation 6 shows a VECM for two variables including a constant, the error correction term and a lagged term.

$$\begin{bmatrix} \Delta p_t^t \\ \Delta p_t^2 \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} ECT_{-1} + \begin{bmatrix} b_{11} \; b_{12} \\ b_{21} \; b_{22} \end{bmatrix} \begin{bmatrix} \Delta p_{t-1}^1 \\ \Delta p_{t-1}^2 \end{bmatrix} + \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^1 \end{bmatrix} \tag{6}$$

Here p_t^1 and p_t^2 stand for two different price market at time t. If the two market prices are integrated then it is reasonable to conduct cointegration and vector error correction analysis (VEC) to examine the joint properties between them. The VECM representation allows for estimating how the variables adjust deviations towards the long-run equilibrium along with error correction coefficient (a_i). The negative coefficients of error correction term (ECT) for the market prices indicate that the deviations would be recovered in the following period.

Consider the residuals which are generated from VEC model as

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} = H_t^{t/2} \begin{pmatrix} \vartheta_{1,t} \\ \vartheta_{2,t} \end{pmatrix} \tag{7}$$

where $\vartheta_t = \begin{pmatrix} \vartheta_{1,t} \\ \vartheta_{2,t} \end{pmatrix}$ ~ $iidN$ (0, $I_{2\times2}$) and $H_t^{1/2}$ is a 2 × 2 positive definite matrix, H_t is the conditional variance matrix of ε_t.

$$\text{Var}\ (\varepsilon_t|\Omega_{t-1}) = Var_{t-1}\ (\varepsilon_t) = H_t^{1/2}\ Var_{t-1}\ \left(\vartheta_t\right)\left(H_t^{1/2}\right) = H_t \tag{8}$$

where Ω_{t-1} is the market information set in period t-1. The MGARCH-BEKK model proposed by Engle and Kroner, includes quadratic forms therefore the conditional variance matrix H_t are positive definite which is necessary for ensuring the estimated variance to be non-negative.

In bivariate case, the variance-covariance matrix H_t can be expressed as

$$H_t = \begin{bmatrix} h_{11,t} \; h_{12,t} \\ h_{21,t} \; h_{22,t} \end{bmatrix} \tag{9}$$

Accordingly, the MGARCH-BEKK (1, 1) representation of variance of error term H_t is

$$H_t = C'C + A'\ 11\ \varepsilon_t - 1\ \varepsilon_t - 1\ A_{11} - B'11\ H_{t-1}\ B11 \tag{10}$$

where, A and B are 2×2 parameter matrix and C is 2×2 upper triangular matrix. The bivariate BEKK(1,1) can be rewritten as:

$$H_t = C'C + \begin{pmatrix} a_{11}\, a_{12} \\ a_{21}\, a_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11}\, a_{12} \\ a_{21}\, a_{22} \end{pmatrix} +$$

$$\begin{pmatrix} b_{11}\, b_{12} \\ b_{21}\, b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1}\, h_{12,t-1} \\ h_{21,t-1}\, h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11}\, b_{12} \\ b_{21}\, b_{22} \end{pmatrix} \quad (11)$$

The off diagonal parameters in matrix B, b_{12} and b_{21} respectively measures the dependence of conditional price volatility in the futures market on that of spot market and vice-versa. The parameters b_{11} and b_{22} represents persistence in volatility in their own market. The parameters a_{12} or a_{21} represent the cross market effects whereas, a_{11}, a_{22} represent the own market effects. Therefore, the significant level of each parameter indicates the presence of strong ARCH or GARCH effect. From the equation 11 we can have the following equations of conditional variance and conditional covariance,

$$h_{11,t} = C_1 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}\, a_{21}\, \varepsilon_{1,t-1}\, \varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2\, b_{11} b21 h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad (12)$$

$$h_{22,t} = C_3 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}\, a_{22}\, \varepsilon_{1,t-1}\, \varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2\, b_{11} b22 h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (13)$$

$$h_{12,t} = C_2 + a_{11}\, a_{12}\, \varepsilon_{1,t-1}^2 + (a_{21}\, a_{12} + a_{11}\, a_{22})\, \varepsilon_{1,t-1}\, \varepsilon_{2,t-1} + a_{21}a_{22}\, \varepsilon_{2,t-1}^2 + b_{11}\, b_{12}\, h_{11,t-1}^2 + (b_{21}\, b_{12} + b_{11}\, b_{22})\, h_{12,t-1} + b_{21}\, b_{22}\, h_{22,t-1}^2 \quad (14)$$

For testing volatility spillover in the volatility equations (9) to (11), if the null hypothesis $a_{12} = b_{12} = 0$ can be statistically rejected, we interpret the rejection as evidence that volatility in second market might be transmitted to the first market. And if $a_{21} = b_{21} = 0$ is significant then volatility transmission in the reverse case (first to second).

According to Engle (2002), the dynamic conditional correlation (DCC) model set up can be expressed in the following manner:

$$H_t = D_t R_t D_t = \rho ijt\sqrt{h_{iit} hj_{jt}} \quad (15)$$

where, H_t is the conditional variance co-variance matrix, R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows:

$$D_t = diag\left(h_{11t}^{\frac{1}{2}}, \ldots, h_{nnt}^{\frac{1}{2}}\right) \quad (16)$$

where h_{iit} is chosen to be a univariate GARCH (1,1) process;

$$R_t = (diagQ_t)^{-1/2}\, Q_t (diagQt)^{-1/2} \quad (17)$$

where $Q_t = (1 - \alpha - \beta)\, \bar{Q} + \alpha u_{t-1}\, u_{t-1} + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = {}^{\varepsilon_{it}}\big/\sqrt{h_{iit}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non negative scalar parameters satisfying $\alpha + \beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets i and j is then computed as follows:

$$\rho ij = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t} u_{j,t-1} + \beta_{qij,t-1}}{(1-\alpha-b)\bar{q}_{ij} + \alpha u_{i,t-1}^2 + \beta_{qii,t-1})^{1/2} \; ((1-a-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1})^{1/2}} \quad (18)$$

where ρ_{ij} refers to the element located in the i^{th} row and j^{th} column of the symmetric positive definite matrix Q_t.

In India more than half of daily arrivals go through the country's top ten onion markets. Among them six out of ten markets located in Maharashtra and Karnataka. Delhi, Gujarat and Rajasthan have one market each. Country's price is largely regulated by those markets participants. Around 45% of the produce comes from the state of Maharashtra and Karnataka. In this study, Mumbai and Nashik markets from Maharashtra and Delhi market from Delhi is considered according to market behaviour. Monthly wholesale price of Onion markets of Mumbai, Nashik, Delhi and Bangalore were collected from the period March, 2003 to September, 2015 from the website of Directorate of Marketing and Inspection (DMI), Ministry of Agriculture, Government of India with a total of 151 data points.

RESULTS AND DISCUSSION

In this study we go for pair-wise analyses to investigate the price transmission mechanism between markets. The Table 1 presents descriptive statistics of the selected markets prices. It can be seen that there is a significance difference between average price of Nashik and other markets prices. In case of Nashik market the price ranges in between 8 to 9 per kg, whereas 10 to 11 per kg in other markets. High instability/volatility of prices has been remained in case of Nashik market (C V 87%) followed by Mumbai, Delhi and Bangalore market. Among these four markets the lowest and the highest price occurred in Nashik (₹ 2.16 per kg during March 2003) and Delhi (₹ 49.22 per kg during September 2013) in the entire duration of March, 2003 to September, 2013 respectively. The skewness value for all the markets show presence of asymmetric behaviour in them and also the coefficient of kurtosis is very high in Nashik followed by Delhi and Mumbai which reflect the leptokurtic distribution and high degree of extreme values.

The seasonality pattern of the markets is reported in Table 2. From this table we can say that the prices of onion

Table 1 Descriptive statistics of selected onion markets

Statistics	Mumbai	Nashik	Delhi	Bangalore
Mean (₹/q)	1035.102	873.283	1053.121	1066.948
Median (₹/q)	767.940	646.040	807.790	802.180
Std. Deviation (₹/q)	811.125	759.784	780.317	733.338
Skewness	2.455	2.869	2.489	1.883
Kurtosis	7.331	10.097	7.673	3.798
Maximum (₹/q)	4744.97	4648.89	4922.26	3831.09
Minimum (₹/q)	236.35	216.75	315.12	344.79
CV (%)	78.36	87.01	74.09	68.73
No. of observation	151	151	151	151

Table 2 Seasonality in Onion arrivals and prices in selected markets of India

Market	Highest		Lowest	
	Arrivals	Price	Arrivals	Price
Mumbai	Dec, Jan, Feb, Mar	Oct, Nov, Dec, Jan	August, May, Sept, Oct	March, April, May, June
Nashik	Dec, Jan, Feb, Mar	Sept, Oct, Nov, Dec, Jan	May, June, July, Aug, Sept	Mar, April, May, June
Delhi	Nov, Dec, March and June	Oct, Nov, Dec and Jan	Jan, Sept, Oct	April, May, June
Bangalore	Sept, Oct, Nov and Jan	Jan, Feb, August	April, March, June, July	March, April and May

markets differ significantly from the average price during August to January whereas in March to April the prices remained below the average price. The overall highest and lowest price can be observed in the month of October and May for all the markets (Table 3). In order to eliminate the influence of seasonality, all the market prices have been adjusted them with seasonal indices. The recent trend of area and production of onion market has depicted in Fig 1 showing ~50% increase in area and ~90% increase in production over the thirteen years while increasing rate in area and production has found after the year 2003-04 and 2009-10, may be due to positive effects of government policy. A graphical representation of actual and seasonally adjusted series for each market has been depicted in Fig 2. The plot shows that prices peaked during the period of 2010, decreased afterwards, but went up again in 2013. The increase in onion prices in 2013 is mainly attributed to production shortfalls due to weather aberration. The other reason may be increasing demand due to steadily increasing world population and an increasing demand for onion with declining rate of agricultural land of onion crop. The reason may be the sharp increase in prices is speculative activity in commodity markets.

It has seen that the price markets are significantly highly correlated with each other implying higher co-movement and greater integration between them (Table 4). In order to check the stationarity, ADF test has been employed to the seasonally data set. The ADF test confirms the presence of unit root in every case but after first differencing of seasonally adjusted series, they are found to be stationary and therefore, they are integrated of order one, i.e. I(1)

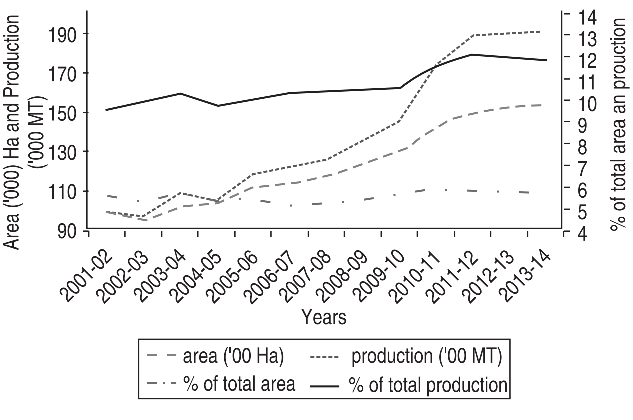

Fig 1 Area and production trend of onion in India (data source: NHB 2014)

Table 3 Seasonal factors of selected onion markets prices

Month	Mumbai	Nashik	Delhi	Bengaluru
January	1.109	1.151	1.144	1.051
February	0.877	0.949	0.975	1.063
March	0.668	0.663	0.840	0.884
April	0.641	0.609	0.704	0.762
May	0.644	0.598	0.634	0.776
June	0.807	0.793	0.696	0.847
July	0.886	0.915	0.893	0.958
August	1.082	1.193	1.101	1.095
September	1.194	1.248	1.217	1.122
October	1.424	1.454	1.441	1.121
November	1.432	1.281	1.277	1.158
December	1.251	1.158	1.092	1.182

Table 4 Correlation of the price series

Market	Mumbai	Nashik	Delhi	Bengaluru
Mumbai	1	0.968 (0.001)	0.962 (0.001)	0.939 (0.001)
Nashik	0.968 (0.001)	1	0.976 (0.001)	0.911 (0.001)
Delhi	0.962 (0.001)	0.976 (0.001)	1	0.934 (0.001)
Bengaluru	0.939 (0.001)	0.911 (0.001)	0.934 (0.001)	1

In parenthesis P-value is given.

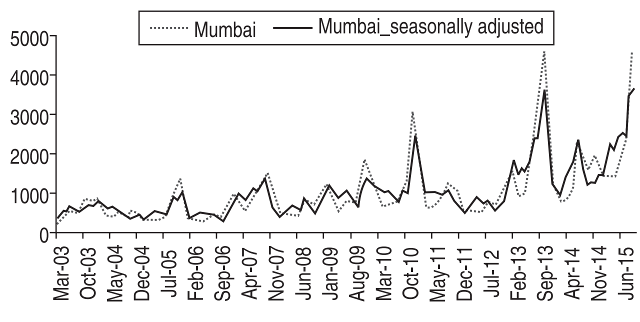

Fig 2 Actual price series (dashed line) and seasonally adjusted series of Mumbai market

Table 5 Stationarity test

Market	Seasonally adjusted series		1stdifference of seasonally adjusted series	
	Unit root statistics	P-value	Unit root statistics	P-value
Mumbai	-1.623	0.468	-8.275	<0.001
Nashik	-2.570	0.101	-8.045	<0.001
Delhi	-2.799	0.070	-8.408	<0.001
Bengaluru	-2.602	0.095	-14.310	<0.001

at 5% significant level (Table 5). This situation allowed proceeding for Johansen's cointegration test.

In order to examine the cointegrating relationship, appropriate VAR order has been identified for every pair of markets on the basis of minimum value of Akaike information criteria (AIC), final prediction error (FPE), likelihood ratio (LR), Schwartz criteria (SC) and Hannan Quinn (HQ) criteria. According to the trace test statistics, the null hypothesis of no cointegration is rejected at 5% significant level against the alternative hypothesis of one cointegration (Table 6). The presence of cointegrating vector reflected the existence of long run relationship between market prices. So there is the presence of information flow between them. The ECT for all markets have been obtained and found significant for Delhi market only among the market pairs of Delhi-Mumbai and Delhi-Bangalore. In these cases the speed of recovery to equilibrium for onion price in Delhi market is similar as the ECT parameters are -0.686 and -0.669 respectively.

Table 7 represents the result on fitted BEKK model. For the price markets, the estimated ARCH parameters are considerably larger than the corresponding GARCH coefficients. This indicates that the, "fresh news" are more influenced by the lagged innovations rather than variances

Table 6 Results of cointegration

Market	Test statistic				
	Lag selection using VAR model	Order of integration	Trace test	Max Eigen value test	Hetero-scedas-ticity test of VECM residuals
Mumbai-Nashik	2	I(1)	1.573 (0.209)	1.572 (0.209)	298.961 (<0.001)
Mumbai-Delhi	2	I(1)	0.607 (0.436)	0.608 (0.436)	275.153 (<0.001)
Mumbai-Bengaluru	4	I(1)	1.847 (0.174)	1.847 (0.174)	294.260 (<0.001)
Nashik-Delhi	8	I(1)	0.014 (0.905)	0.014 (0.905)	226.251 (<0.001)
Nashik-Bengaluru	3	I(1)	1.193 (0.274)	1.194 (0.275)	229.949 (<0.001)
Delhi-Bengaluru	3	I(1)	0.716 (0.397)	0.715 (0.396)	279.777 (<0.001)

In parenthesis P-value is given.

Table 7 Results of BEKK model

Coefficients	Mumbai/ Nashik	Delhi/ Nashik	Delhi/ Mumbai	Bengaluru/ Mumbai	Bengaluru/ Nashik
c_{11}	11.346	169.895***	124.986***	160.306***	190.071***
c_{21}	12.675	120.668*	146.968	113.709***	108.392***
c_{22}	7.617***	49.303*	31.084	37.908	39.073
a_{11}	0.561*	0.254·	0.472***	0.001	0.174*
a_{21}	-0.260	0.496***	-0.021	-0.338**	0.249***
a_{12}	0.043	0.453***	0.146	0.500*	0.277*
a_{22}	0.929***	0.001	0.001	0.981***	0.821***
b_{11}	0.151*	0.116	0.884	0.003	0.001
b_{21}	-0.500***	-0.500*	0.500	-0.378**	-0.452**
b_{12}	-0.245^	0.501	-0.417	0.500***	-0.500***
b_{22}	0.350***	0.001	0.218	0.001	0.381**

Indicates significant at 10%, *indicates significant at 5%, ** indicates significant at 1%, ***indicates significant at 0.1%

of these prices that are reflected by their own lagged values. For the market pairs of Bangalore-Mumbai and Bangalore-Nashik, the coefficients for the variance covariance equations are generally significant for own and cross innovations, and significant for cross volatility spillovers indicating presence of strong ARCH and GARCH effects. In evidence 62% (15 out of 24) of the estimated ARCH coefficients and 42% (10 out of 24) of the estimated GARCH coefficients are significant at 5% and 1% level of significance.

Almost every cross market innovations are significant except Delhi/Mumbai and Mumbai/Nashik. All the coefficients are insignificant in case of Delhi/Bangalore market except a_{12} and a_{22} which are 0.482 and 0.345 respectively. The own innovation spillover in Nashik market appears large and significant in most of the cases, indicating the presence of strong ARCH effects which ranges from 0.821 to 0.929 for Bangalore and Mumbai market respectively. Similarly, the own innovation spilloverof Mumbai market ranges from 0.561 to 0.981 for Nashik and Bangalore market respectively.The findings also suggest that Nashik market is the main transmitter of volatility which is -0.500 for Mumbai as well as for Delhi and -0.452 for Bangalore market respectively. The coefficient is insignificant in case of the market pairs of Delhi-Mumbai and Delhi-Nashik at 5% level of significance. The presence of bidirectional shock and volatility spillover reflects in case of Bangalore-Mumbai and Bangalore-Nashik markets. The diagnostic test of the fitted BEKK model has been verified using Ljung Box test of serial correlation and was found to be significant (Table 8).

The changing pattern of dependence of these price markets are reported from Fig 3. The DCC model results the presented in Table 9. In all cases the DCC shows positive behavior which reflect the direct time varying positive relation between the markets (i.e. increase in volatility of one market leads to increase in volatility of the other market). The DCC between Mumbai and Nashik market varies from

Table 8 Diagnostic test

L-Jung Box Test	Test statistics value	P-value
Mumbai/Nashik	0.883	0.988
Delhi/Nashik	14.389	0.156
Delhi/Mumbai	3.0358	0.980
Bengaluru/Mumbai	9.619	0.475
Bengaluru/Nashik	10.069	0.434
Delhi/Bengaluru	11.473	0.322

Table 9 Results of DCC model

Estimate	Mum/Nas	Nas/Del	Del/Mum	Mum/Beng	Nas/Beng	Del/Beng
μ_1	9.494 (0.564)	3.073 (0.852)	18.542 (0.183)	734.310 (<0.001)	553.540 (<0.001)	626.359 (0.361)
μ_2	3.073 (0.853)	21.457 (0.157)	5.335 (0.686)	659.730 (0.001)	659.730 (0.001)	638.403 (<0.001)
ω_1	2779.605 (0.565)	2406.900 (0.351)	7792.480 (0.003)	9376.200 (0.054)	6516.300 (0.149)	7326.820 (0.045)
ω_2	2406.861 (0.350)	7189.400 (0.005)	3235.973 (0.643)	12728.000 (0.508)	12728.000 (0.507)	4835.327 (0.328)
α_1	0.354 (0.0001)	0.328 (0.002)	0.699 (<0.001)	0.592 (<0.001)	0.592 (<0.001)	0.629 (0.008)
α_2	0.328 (<0.001)	0.659 (<0.001)	0.368 (<0.001)	0.546 (0.012)	0.546 (0.008)	0.328 (0.010)
β_1	0.645 (<0.001)	0.671 (<0.001)	0.299 (0.001)	0.407 (<0.001)	0.406 (<0.001)	0.369 (0.030)
β_2	0.671 (<0.001)	0.339 (<0.001)	0.630 (0.001)	0.453 (<0.001)	0.453 (<0.001)	0.671 (<0.001)
δ_{DCC1}	0.076 (0.043)	0.068 (0.149)	0.104 (0.009)	0.129 (0.012)	0.905 (0.017)	0.0001 (0.998)
δ_{DCC2}	0.556 (0.013)	0.837 (<0.001)	0.422 (0.029)	0.772 (<0.001)	0.765 (<0.001)	0.918 (<0.001)

In parenthesis P-value is given

0.6 to 0.9, which represents a highly time varying nature persist in between them. The main reason for the difference between constant and dynamic correlations is may be due to the presence of sharp peaks in the year of 2010 and 2013. In case of Mumbai/Bangalore and Nashik/Bangalore, the DCC pattern is almost same reflecting the similar time varying dependency pattern. These results confirm that there is a strong evidence of time varying correlations among the selected onion markets. Finally the validity of the DCC model was verified using Lagrange Multiplier (LM) test for serial correlation and was found significant.

In this study we try to examine the pattern of volatility spillover under VEC-MGARCH model for onion markets of Mumbai, Nashik, Bangalore and Delhi. The time varying nature of dynamic conditional correlation was found significant under DCC model set up. Our estimated results provide the evidence about how shocks and volatility are transmitted from one market to another. The results confirmed the absence of volatility spillover in between the markets of Delhi/Mumbai and Delhi/Bengaluru (though they are highly correlated) but found the evidence of price shock transmission. Bidirectional shock and volatility spillover was found in case of Bangalore/Mumbai and Bangalore/Nashik markets. In this aspect, this type of significant interaction between the volatility of different markets is highly useful for cross market hedging and for sharing of common information by market participants. The empirical results also suggest for a very close observation on different market behavioral pattern since, "news" in one market may impact other market through the number of interdependencies.

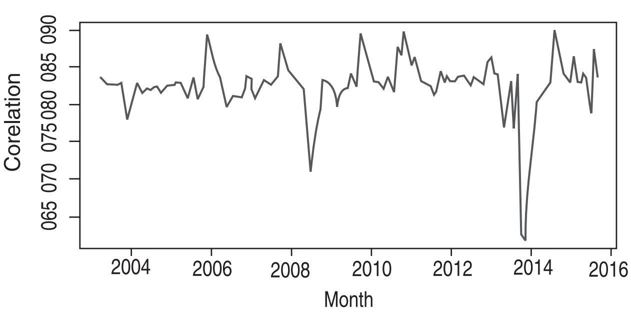

Fig 3 Dynamic conditional correlation between Mumbai and Nashik market

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